



Classification of Satellite Images

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Abstract:

Satellite imagery is important for many applications including disaster response, law enforcement, and environmental monitoring. These applications require the manual identification of objects and facilities in the imagery. Because the geographic expenses to be covered are great and the analysts available to conduct the searches are few, automation is required. Yet traditional object detection and classification algorithms are too inaccurate and unreliable to solve the problem. Deep learning is a family of machine learning algorithms that have shown promise for the automation of such tasks. It has achieved success in image understanding by means of convolutional neural networks (CNNs). Also, there has been a massive growth in Deep learning in many fields such as computer vision and natural language processing. But, still there exists a lack of deep review for the datasets and methods available for scene classification from the satellite imagery. This paper focuses on enlightening the concept and evolution of Deep Learning.

Keywords: Deep Learning, Image Processing, Data set, Python, CNN, Classification of Satellite Images.

I. INTRODUCTION

Image classification is an important part of remote sensing, image analysis and pattern recognition. In some instances, the classification itself may be the object of the analysis. For example, classification of land use from remotely sensed data produces a map-like image as the final product. The image classification therefore forms an important tool for examination of digital images. At present, there are different image classification procedures used for different purposes by various researchers. Over the last decade, remote sensing technologies are available easily and in abundance. Recently remote sensing images are being used widely for urban area classification and change detection. Classification is used for various applications like Crop monitoring (crop condition, crop type, and crop production estimation), Soil mapping characteristics (soil type, soil erosion and soil moisture), Forest cover mapping differences (leaf density, canopy texture), Land cover change detection (seasonal and annual changes), Natural disaster assessment (flood, cyclone and heavy raining), Water resource applications, wetland mapping, and environment inventory, urban and Regional planning and similarly other objects of interest can be observed using the remote sensing data. The selection of a suitable classifier to process the satellite images has an important role with respect to the efficient and accurate classification results. In this work, we are creating a system to classify satellite images in order to extract information using image processing techniques. Classification of satellite images into used and unused areas and also sub-classing of each of the classes into four different classes has been carried out. Used satellite images are further classified into residential, industries, highways, crop lands, and unused images are classified further into forest, river, deserts, and beaches. Manual classification by using image interpretation techniques requires more time and field experts. So in our work, we focused on efficient automatic satellite image classification. Convolutional neural networks are used for feature extraction and classification of satellite images.

CNN is a deep neural network which is most suitable when we deal with images. CNN will help to provide higher classification accuracy. Confusion matrix is used to estimate the overall classification accuracy. Deep learning is a class of machine learning models that represent data at different levels of abstraction by means of multiple processing layers. It has achieved astonishing success in object detection and classification by combining large neural network models, called CNN with powerful GPU.

CNN-based algorithms have dominated the annual ImageNet Large Scale Visual Recognition Challenge for detecting and classifying objects in photographs. This success has caused a revolution in image understanding, and the major technology companies, including Google, Microsoft and Facebook, have already deployed CNN-based products and services. Satellite image classification is the most significant technique used in remote sensing for the computerized study and pattern recognition of satellite information, which is based on diversity structures of the image that involve rigorous validation of the training samples depending on the used classification algorithm. It is an extreme part of remote sensing that depends originally on the image resolution, which is the most important quality factor in images. Image Classification or segmentation is a partitioning of an image into sections or regions.

The power of such algorithms depends on the way of extracting the information from the huge amount of data found in images. Then, according to this information, pixels are grouped into meaningful classes that enable to interpret, mining, and studying various types of regions that are included in the image. Many applications based on using Landsat imagery in a quantitative fashion require classification of image pixels into a number of relevant categories or distinguishable classes. Image classification or land use/land cover classes were identified using supervised/pixel-based/image classification techniques. Image classification is the process of creating thematic maps from satellite imagery. A thematic map is an information representation of an image that shows the spatial distribution of a particular theme.

II. RELATED WORK:

NurAnis Mahmon et al. [1] reviews the capability of ANNs to classify image satellites with various ANNs approaches [1]. The classification takes different time to classify because the number of data training sets is dependent on the algorithm neural network model and number of classes. This paper also reviewed various techniques applicable for classification of satellite images to be compared with ANNs according to the value of accuracy assessment. The comparison of these techniques also will be validated with the datum, this study approaches the best techniques to classify the land use and land cover with various approaches of classification techniques. At the last output the LU/LC map of the study area can indeed be applied for a variety of purposes such as deforestation, archaeology, weather forecasting, urban planning, development, damage assessment etc. Mark Pritt et al. [5] reviews combined with a detection component, system could search large amounts of satellite imagery for objects or facilities of interest. In this way it could solve the problems posed at the beginning[5]. By monitoring a store of satellite imagery, it could help law enforcement officers detect unlicensed mining operations or illegal fishing vessels, assist natural disaster response teams with the mapping of mudslides or hurricane damage, and enable investors to monitor crop growth or oil well development more effectively. Sayali Jog et al. [6] proposed analysing and comparing supervised classifiers namely minimum distance, support vector machine, maximum likelihood, and parallelepiped, it is indicated that for different types of images maximum likelihood classifier gives better results in terms of kappa coefficient and overall accuracy than minimum distance and parallelepiped classifier. Overall accuracy is greater than 88% and kappa statistics is greater than 0.82 for maximum likelihood classifier for all types of images except Landsat MSS images. Overall accuracy for SVM is more than 92% for both kernels. Sigmoid function and radial basis function can be used to improve the accuracy of SVM [6].

M. P. Vaishnav et al. [2] reviews extensive comparative study has been given on various methods available in deep learning. Then, by analysing the existing literature for deep learning, this paper discusses some literature gaps to enable the research community to develop new data-driven algorithms. And it provides some state-of-art quantitative metrics such as accuracy, precision, recall and F1 score for evaluating the satellite Imagery scene classification. All the additional information will be very much useful for image classification and recognition of satellite Imagery as it could help the users to learn important feature representations. Consequently, in the future we need to explore new data-driven algorithms and deploy it to promote the state-of-art of satellite Imagery scene classification [2].

Gong Cheng et al. [3] proposed comprehensive reviews of the recent progress in the field of remote sensing image scene classification, including benchmark datasets and state-of-the-art methods.

Then, by analysing the limitations of the existing datasets, proposed a large-scale, freely and publicly available benchmark dataset to enable the community to develop and evaluate new data-driven algorithms. Finally, evaluated a number of representative state-of-the-art methods including deep learning-based methods for the task of scene classification using the proposed dataset and reported the results as a useful performance baseline for future research [3].

III. PROBLEM STATEMENT:

To segment and detect the images received from satellites by using a deep learning system and image processing which classifies objects and facilities in high-resolution multi spectral satellite imagery.

IV. ARCHITECTURAL OVERVIEW:

A CNN consists of a series of processing layers as shown in Fig 1. Each layer is a family of convolution filters that detect image features. Near the end of the series, the CNN combines the detector outputs in fully connected “dense” layers, finally producing a set of predicted probabilities, one for each class. The network itself learns which features to detect, and how to detect them, as it trains.

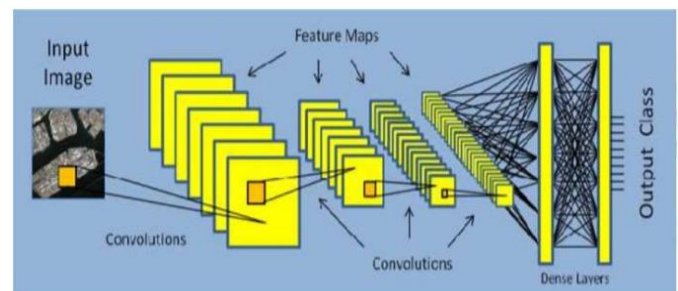


Figure.1. Architecture of Satellite Image classification.

General Framework:

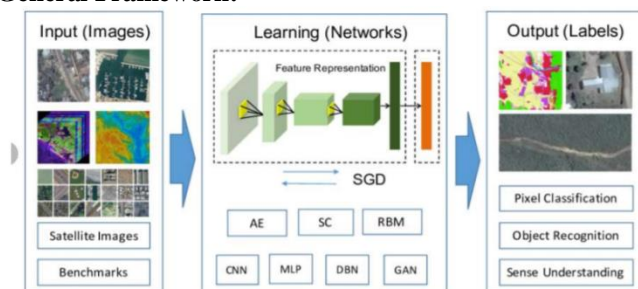


Figure.2. Architecture overview of Classification of satellite images

The general Framework of Deep Learning based method for satellite image classification can usually be described as three components: prepared input data, deep networks and expected output, as shown in Figure. The input data include different kinds of satellite images datasets (i.e. benchmarks used for training), while the output is the manually defined label of the pixels per land corner type of upsell and the object type in the image tiles. The deep networks we stacked by multiple outliner neural layers, where such intermediate layer model input data to features encodes low level features to high-based features, the parameters of are usually learned by DL model like an AI unlabelled training images, while the overall parts are fine-tuned by algorithms like Stochastic Gradient Descent (SGD) with the supervision of label training. Satellite image classification with Deep Learning where classic deep networks like CNNs, Multiplayer Perceptions (MLPs) and Deep Belief Networks (DBNs) as well as feature learning algorithms like AEs, Restricted Boltzmann Machines (RBMs) and Sparse Coding (SC) are introduced and the studies are classified into four kinds according to the purpose, namely image pre-processing, pixel-based classification, target recognition and scene understanding. Except for the above deep networks, we supplement another unsupervised deep model named Generative Adversarial Networks (GANs) which have been widely explored.

V. DATASETS:

We have used Kaggle dataset, which contains 45000 plus images. The provided dataset has images of different dimensions. So, we have used various techniques to pre-process the dataset. For training the model, we split the dataset into a training, testing and validation set. Ideally, we should have split the dataset into training, validation and test dataset but due to the limited size of the dataset we are splitting it into two. This split is done, and the training dataset is used to train the model and validation set is used for testing the test accuracy, as the model performance is more reliable on a completely unseen dataset. Test accuracy of a model largely depends on the size (No. of images used for training) and quality of images. Therefore, all noisy and corrupted data points must be removed from the dataset and one very popular dataset is Kaggle dataset. The images in this dataset are not taken in the controlled lab environment, and therefore most of the images are having low contrast and noise present.

VI. SYSTEM DESIGN OF CLASSIFICATION OF SATELLITE IMAGES

A major motivation for undertaking this work was to gain an understanding for designing, implementing and evaluating a deep learning pipeline with the focus on satellite image data. This was defined as a semantic segmentation problem, to identify roads and buildings in areas.

Pre-processing: This is the first step performed in image processing.

Segmentation: It is used to convert input images.

Merging: The aim of Merging is to allow the merge of pattern which is most important for the classification. All of these features are used to train the given system.

Classification: The decision making is done in the classification phase. For recognizing satellite images, the extracted features are used.

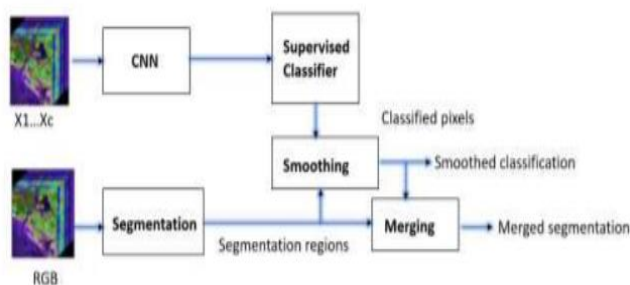


Figure.3. System Design of classification of satellite Images

Instance Segmentation:

- We take an image as input and pass it to the ConvNet, which returns the feature map for that image
- Region proposal network (RPN) is applied on these feature maps. This returns the object proposals along with their objectness score
- A RoI (Region of interest) pooling layer is applied on these proposals to bring down all the proposals to the same size
- Finally, the proposals are passed to a fully connected layer to classify and output the bounding boxes for objects. It also returns the mask for each proposal

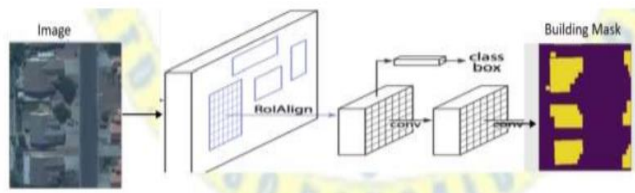


Figure.4. Mask R-CNN for instance Segmentation.

This challenge is provided with a dataset of individual tiles of satellite imagery as RGB images, and their corresponding annotations of where an image is there of a building. The goal is to train a model which, given a new tile, can annotate all buildings. Also, in context of this challenge, to make the barrier to entry much lower, we tried to remove all the domain specific jargon of Remote Sensing and Satellite Imagery Analysis, and are presenting this as a problem of Object Detection and Object Segmentation in Images. The idea being, once we collectively demonstrate that an approach works really well on RGB images with just 3 channels of information, we can then work on extending it to multi-channel information from rich satellite imagery.

VII. EXPERIMENT RESULTS:



Figure.5. Visualizing Building Mask



Figure.6. Visualizing results on augmented results

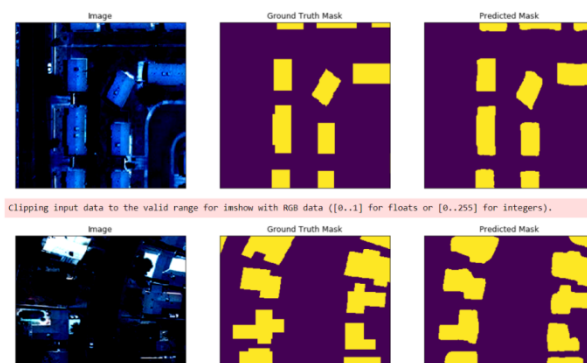


Figure.7. Visualizing results on random validation results

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Epoch: 1
train: 100% [██████████] 752/752 [09:43<00:00, 1.291t/s, dice loss - 0.114, iou score - 0.7968]
valid: 100% [██████████] 41/41 [00:18<00:00, 3.95t/s, dice loss - 0.1099, iou score - 0.8039]
Model saved!

Epoch: 2
train: 100% [██████████] 752/752 [09:47<00:00, 1.281t/s, dice loss - 0.1119, iou score - 0.7999]
valid: 100% [██████████] 41/41 [00:18<00:00, 4.10t/s, dice loss - 0.1096, iou score - 0.8042]
Model saved!

Epoch: 3
train: 100% [██████████] 752/752 [09:36<00:00, 1.301t/s, dice loss - 0.1114, iou score - 0.8088]
valid: 100% [██████████] 41/41 [00:09<00:00, 4.26t/s, dice loss - 0.1095, iou score - 0.8046]
Model saved!

Epoch: 4
train: 100% [██████████] 752/752 [09:38<00:00, 1.301t/s, dice loss - 0.1208, iou score - 0.7863]
valid: 100% [██████████] 41/41 [00:09<00:00, 4.11t/s, dice loss - 0.1086, iou score - 0.8065]
Model saved!

Epoch: 5
train: 100% [██████████] 752/752 [09:36<00:00, 1.301t/s, dice loss - 0.1144, iou score - 0.7963]
valid: 100% [██████████] 41/41 [00:09<00:00, 4.26t/s, dice loss - 0.1087, iou score - 0.8062]
```

Figure.8. Epochs Training

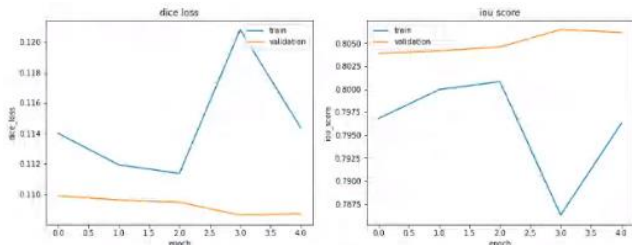


Figure.9. Dice loss and accuracy of the system.

VIII. INCORPORATED LIBRARIES AND PACKAGES

A. Pandas is a Python library used for working with data sets. It has functions for analyzing, cleaning, exploring, and manipulating data. Pandas allows us to analyze big data and make conclusions based on statistical theories. Pandas can clean messy data sets, and make them readable and relevant.

B. Matplotlib is a low level graph plotting library in python that serves as a visualization utility. Matplotlib is open source and we can use it freely.

C. Pillow, the Python Imaging Library adds image processing capabilities to your Python interpreter. This library provides extensive file format support, an efficient internal representation, and fairly powerful image processing capabilities.

D. Albumentations is a Python library for image augmentation. Image augmentation is used in deep learning and computer vision tasks to increase the quality of trained models. The purpose of image augmentation is to create new training samples from the existing data.

E. PyTorch is a Python package that provides two high-level features, Tensor computation (like NumPy) with strong GPU acceleration and Deep neural networks built on a tape-based autograd system.

F. The torchvision package consists of popular datasets, model architectures, and common image transformations for computer vision.

G. EfficientNet PyTorch is a PyTorch re-implementation of EfficientNet. It is consistent with the original TensorFlow implementation, such that it is easy to load weights from a TensorFlow checkpoint. At the same time, we aim to make our PyTorch implementation as simple, flexible, and extensible as possible.

H. Segmentation-models-PyTorch is a Python library with Neural Networks for Image segmentation based on PyTorch.

IX. PROPOSED SYSTEM

It uses recent advances approach for classification of satellite images. A new spatial unit of analysis is used and series evaluation is conducted. Segmentation process is quite low where larger data set is used. It presents the good data set with labelled scene. The task outlined is to use computer vision to automatically extract building footprints from satellite images in the form of vector polygons (as opposed to pixel maps). Predictions generated by a model are determined viable or not by calculating their intersection over union with ground truth footprints. When we run an image through the model, it outputs a series of coordinates that define the boundaries of the building footprints we are looking to find as well as a mask on which these footprints are plotted. The process of visualizing an image and its mask side-by-side to get a sense of how effective the model is at extracting building footprints. Getting a coherent visual

representation of the data is somewhat trickier than expected. This is because each pixel in a given image is assigned 4 values, corresponding to 4 polarizations of data in the X-band of the electromagnetic spectrum. In short, signals transmitted and received come in both horizontal and vertical polarization states, so each channel corresponds to a different combination of the transmitted and received signal types. These 4 channels don't translate to the 3 RGB channels we expect for rendering a typical image. With this, we can see that the model did recognize the general shapes of several buildings.

X. CONCLUSION

This system presents a deep learning system that classifies objects and facilities in high-resolution multi-spectral satellite imagery. The system consists of an ensemble of CNNs with post processing neural networks that combine the predictions from the CNNs with satellite metadata. Additionally, the image processing is important and different stages of it such as filtering of bands and principal component analysis should be applied before evaluation. All these points were applied to this study and it has been seen that maximum likelihood classifier was the most suitable classification method for land use mapping purposes. Minimum distances classifier was also determined as suitable as the maximum likelihood classifier.

XI. REFERENCES

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